Deep Learning for Climate Model Output Statistics

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Motivation

• Numerical climate models provide important information for the prospective effects of climate change
• But they also suffer from **systematic errors** and **deficiencies in climate process representation**
• **Model output statistics (MOS)** use statistical techniques to reduce these errors
• Can MOS based on deep learning reduce these errors further?

Source: https://str.llnl.gov/december-2017/bader
Outline

• Model Output Statistics (MOS)
• Deep Learning for Climate MOS: ConvMOS
• Experiment
• Results
• Conclusion & Future Work
Model Output Statistics (MOS)

• Goal: Correct modeled climate variable (e.g. precipitation) to correspond more closely to observational data

• Previously published approaches:
  • Linear Regression ([Paeth 2011], [Eden et al. 2014])
  • Random Forests ([Sa’adi et al. 2017], [Noor et al. 2019])
  • Support Vector Machines ([Sa’adi et al. 2017], [Pour et al. 2018], [Ahmed et al. 2019])
  • Multilayer Perceptrons ([Moghim et al. 2017])

• Study area often represented as a 2D grid of locations
  → Typically one MOS model per location of interest
Deep Learning for Climate MOS

• What types of errors are there in climate models?
  • Location specific errors
  • Systematic errors

• How to efficiently reduce both types of errors?
  • Combination of per-location model parameters (location specific errors) and global model parameters (systematic errors)

• Two types of modules:
  • Local network
  • Global network
Deep Learning for Climate MOS

Local Network
- Linear regression per location/cell
- Implemented with a 1D CNN
  - Easy integration into architecture
  - 1 Filter per location (groups = $C_{in}$)

Global Network
- 2D CNN
- Activation: ReLU
- Padding: Keep height/width same

$C_{in} = \# \text{ input channels} = \# \text{ number of predictors}, \ H = \text{Height}, \ W = \text{Width}$
ConvMOS

Climate Variable Auxiliary Predictors
Local Network
Adjusted Climate Variable Auxiliary Predictors Elevation
Global Network
Adjusted Climate Variable Auxiliary Predictors
Local Network
Corrected Climate Variable
Experiment

• Apply MOS for **daily precipitation** data of the climate model **REMO**
  • Study area: Extended German region at 0.11° resolution (−1.43° to 22.22° E and 42.77° to 57.06° N)
  • **23 predictors** per cell (e.g. precipitation, temperature, wind, …)
  • Predictand: Observed precipitation from the **E-OBS 19.0e** dataset

• Baseline MOS approaches for comparison:
  • Local linear regression (Lin)
  • Non-local Principal Component Regression (NL PCR)
  • Non-local Random Forest (NL RF)
## Results

<table>
<thead>
<tr>
<th>MOS</th>
<th>Metric</th>
<th>RMSE</th>
<th>Corr.</th>
<th>Skill</th>
<th>$R^2$</th>
<th>Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td></td>
<td>5.32</td>
<td>0.49</td>
<td>0.93</td>
<td>−28.24</td>
<td>0.31</td>
</tr>
<tr>
<td>Lin</td>
<td></td>
<td>3.77</td>
<td>0.49</td>
<td>0.93</td>
<td>0.23</td>
<td>0.03</td>
</tr>
<tr>
<td>NL PCR</td>
<td></td>
<td>3.37</td>
<td>0.62</td>
<td>0.92</td>
<td>0.36</td>
<td><strong>0.02</strong></td>
</tr>
<tr>
<td>NL RF</td>
<td></td>
<td>3.39</td>
<td>0.61</td>
<td>0.81</td>
<td>0.36</td>
<td>0.03</td>
</tr>
<tr>
<td>ConvMOS</td>
<td></td>
<td><strong>2.99 ± 0.01</strong></td>
<td><strong>0.72 ± 0.00</strong></td>
<td>0.92 ± 0.00</td>
<td><strong>0.49 ± 0.01</strong></td>
<td>−0.10 ± 0.06</td>
</tr>
</tbody>
</table>

*Note: RMSE and Bias in mm, other metrics without unit*
Results (RMSE in mm)

(a) REMO raw

(b) ConvMOS
Conclusion & Future Work

• Our work shows good results for Deep Learning MOS
  → Further work in this direction is promising
• Improved MOS allows for more accurate climate data especially at high spatial resolutions
  → More accurate information on prospective effects of climate change

• Future Work:
  • Further analysis
  • Additional comparisons (different study areas, different climate variable, …)
  • Incorporate time
Thank you for your attention